

## RESEARCH ARTICLE

## OPEN ACCESS

## DUAL-STREAM VGG-DINAT FRAMEWORK WITH RED-CROWNED CRANE OPTIMIZATION FOR HAIR AND SCALP DISORDER DIAGNOSIS

Vimala Ithayan J<sup>1\*</sup>, Dilip Charaan R M<sup>2</sup>, Vijayanandh T<sup>3</sup>, Santhoshkumar S P<sup>4</sup>, Parvathi R<sup>5</sup>, Sivaprakash P<sup>6</sup>

<sup>1,2</sup>Associate Professor, School of Computing, Vel Tech Rangarajan Dr Sagunthala R&D Institute of Science and Technology, Chennai, India-600062.

<sup>3</sup>Associate Professor, School of Electrical and Communication, Vel Tech Rangarajan Dr Sagunthala R&D Institute of Science and Technology, Chennai, India-600062.

<sup>4</sup>Assistant Professor (SG), School of Computing, Vel Tech Rangarajan Dr Sagunthala R&D Institute of Science and Technology, Chennai, India-600062.

<sup>5</sup>Associate Professor Grade 1, School of Computer Science Engineering and Information Systems, Vellore Institute of Technology, Katpadi, Vellore, India-632014.

<sup>6</sup>Professor, School of Electrical and Communication, Vel Tech Rangarajan Dr Sagunthala R&D Institute of Science and Technology, Chennai, India-600062.

<sup>1</sup><http://orcid.org/0009-0000-8157-2139>, <sup>2</sup><http://orcid.org/0009-0001-8996-8987>, <sup>3</sup><http://orcid.org/0009-0004-0166-9408>

<sup>4</sup><http://orcid.org/0009-0007-8835-0505>, <sup>5</sup><http://orcid.org/0000-0002-6633-9897>, <sup>6</sup><https://orcid.org/0009-0008-7999-0022>

E-mail: \*[vimalaithayanj@yahoo.com](mailto:vimalaithayanj@yahoo.com)

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## ABSTRACT

In dermatological health care, accurate and reliable diagnosis of hair and scalp conditions is essential; however, traditional diagnostic processes often face challenges related to noise, variability in image quality and limited size datasets. To address these challenges, the present study describes a new Deep Learning (DL) framework that provides improved diagnostic accuracy. To offer effective noise suppression while retaining structural information, input images are augmented or enhanced by using a Spatially Adaptive Non-Local Means (SANLM) filtering based preprocessing model. An Edge-Guided Gaussian Mixture Model (EG-GMM) is then used for segmentation: the ability of the EG-GMM is to very accurately delineate the scalp and hair. To address limited data, a Progressive Growing GAN (PGGAN) model is used for creating realistic data augmentation to improve training variability. For robust classification, a dual stream classifier consisting of VGG19 and the Dilated Neighbourhood Attention Transformer (DiNAT) is used to maximise both long-range contextual attention and spatial feature extraction. For hyperparameter tuning of the framework RCCO (Red-Crowned Crane Optimisation) is employed to ensure improved classifier performance. The experimental validation in python software, demonstrates that the framework outperforms existing models in precision, accuracy, recall, FI-Score of 0.9929 and improved generalisation.



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## I. INTRODUCTION

Due to stress, dietary modifications, and exposure to toxic environmental agents, scalp and hair diseases have become common. The most common symptoms of scalp and hair disorders are dryness, oiliness, erythema, folliculitis, and dandruff [1]. There is a wide range of scalp and hair disorders, including protests such as alopecia and dandruff, to more serious disorders like psoriasis or folliculitis decalvans. These impact an individual's physical wellbeing, but often have psychosocial implications too [2]. Consequently, identifying different scalp and hair conditions as early as possible and undergoing proper hair and scalp treatments guided by an accurate diagnosis is essential. Furthermore, the size of the global scalp and hair care market was valued at USD 91.60 billion in 2022 and is predicted to have an average yearly growth of 5.8% with the rise in demand for hair and scalp health care [3], [4]. A lot of patients do not know whether their hair loss issue is related to stress or seasonal hair loss or if has medical implications. The diagnosis of hair and scalp disorders has historically been based on a dermatologist's clinical exam, history, and then a variety of diagnostic adjuncts [5].

Dermoscopy, for example, has been a mainstay in dermatologic diagnosis, taking advantage of a non-invasive approach to view the follicles and microstructures of the scalp and hair. But the interpretation of dermoscopic images is quite subjective, and occurs based on the examiner's experience and familiarity [6]. While biopsy provides definitive evidence, this is invasive, and typically not the first step in the diagnostic workup [7]. All of these subjective diagnostic methods contribute to large variability in diagnoses. Variability occur, and even significant differences, despite any pre-sent displaying of symptoms. Misdiagnosis lead to improper treatments, or the potential for harm, prolonged distress for patients, and unnecessary healthcare costs [8], [9]. The development of imaging techniques has led to the availability of more advanced instruments such as high-resolution ultrasonography and magnetic resonance imaging that allow for detailed visualization of hair and scalp. These improvements do pose some challenges however [10]. Figure 1 illustrates the clinical images of common pediatric hair and scalp disorders. Interpretation of the images remains subjective, and the high cost and access of advanced imaging tools limits their use in practice. Another challenge is a lack of available datasets, especially for rare or complex conditions and this limits the testing and development of more advanced diagnostic tools [11], [12].



Figure 1: Clinical images of common hair and scalp disorders.

Source: Authors, (2026).

A typical diagnosis requires a dermatologist and hair specialist to visually assess and sometimes carry out medical tests to confirm if there is a diagnosis of disease [13]. For individuals in distant locations, such assessments may not be possible, and are cost prohibitive or time prohibitive [14]. In such cases discovery and treatment could be delayed and lead to progressive worsening of the problem, justifying permanent hair loss and serious hair loss. Doctors are investigating the possibility of utilizing DL in relation to the ever-increasing demand for automated and effective diagnostic methods in health care applications [15]. This research implements a dual-stream VGG-DiNAT framework with red-crowned crane optimization which includes various stages such as preprocessing, segmentation, data augmentation and classification. Here the input dataset undergoes preprocessing to reduce noise, thereby bilateral filter is used to smooth images and at the same time preserve important edges for diagnostic purposes, like hair strands and lesion borders [16]. It is easy to deploy and does not need training data to utilize, which is appealing for basic computational diagnosis. Nevertheless, there are visible costs associated with using it for scalp images with high resolution and, it will not perform adequately when the noise level is high, and the density of hair is inconsistent. To tackle this limitation, SANLM is implemented in the proposed system. The preprocessed image is fed to the segmentation stage, where it effectively isolates relevant anatomical regions [17], [18]. Fuzzy C-Means method permits each pixel to be part of different clusters with various levels of membership, leading to more fluid segmentation of regions that have dandruff, alopecia patches, inflammation, or pigment disorders. The FCM works on areas where the intensity varies gradually as well. However, it is very sensitive to noise, particularly in images that have dense or overlapping hairs, which result in inaccuracies in boundaries and misclassification [19]. To mitigate this issue EG-GMM is proposed in this research. The segmented image is then passed to data augmentation stage which is used to address data imbalance and improve model robustness. A classical GAN broaden restrictive clinical datasets by generating varied artificial scalp images that will prevent overfitting and permit models to learn general variations in the texture of hair strands and scalp locations without labeled data [20]. Nonetheless, it suffers from the problems of mode collapse, low resolution, and instability during training. Therefore, PGGAN method is implemented in this research to resolve this shortcoming [21]. Next, the classification task is performed for high-performance feature extraction and decision making. The related works explain the existing classification methods for hair and scalp disorder diagnosis.

## II. RELATED WORKS

According to [22] have proposed a CNN based Machine learning method for hair and scalp disease detection. Their comprehensive hierarchical structures allow them to effectively classify complicated disorders affecting the scalp. CNNs are also able to better handle noise in images, differences in uniform illumination, and overlapping hairs using convolution and pooling. However, they are computationally expensive, requiring a powerful GPU and a long time for training. In [23] have developed a reimagining scalp disorder analysis through ViT-B/16, a DL and interpretable AI. The ability to capture global relationships of images, model long-range dependence, and a high discrimination of complex scalp textures without convolutional filters. Though, it needs very large datasets for stable training and is sensitive to small medical datasets. According to [24] have presented a detection and classification of alopecia areata using diverse feature set. Combining texture, color, geometrical, and deep features improves the ability to recognize patchy hair loss patterns and distinguish alopecia areata from related scalp diseases, making the detection and classification of alopecia areata using a diverse feature set highly advantageous. Nevertheless it also makes the system more complex, necessitates a lot of preprocessing, and might require laborious feature fusion or selection. According to [25] have established a DL approach for diagnosing hair damage using Scanning Electron Microscopy (SEM) images.

It provides automatic feature extraction, high sensitivity, and reliable performance while requiring little human assistance. Nonetheless, it requires specialized SEM imaging equipment, large annotated training datasets, and high computational requirements. According to [26] have suggested a classification of hair disease using CNN with VGG-16 architecture. VGG-16 has deep hierarchical feature extraction is great at identifying subtle texture changes, follicular patterns, and structures of lesions in images of the scalp. Conversely, it is less architecturally efficient than newer lightweight or transformer-based models, and may have difficulties when the dataset is highly imbalanced or includes rare scalp diseases.

## II.1 OBJECTIVES

The main objectives of this research includes:

- To remove noise and to enhance image quality, preprocessing technique called SANLM is implemented in the proposed system for accurate analysis.
- To develop a robust segmentation and to extract the relevant hair or scalp regions, EG-GMM technique is utilized.
- To overcome data scarcity issues and for improving training diversity, PGGAN method is executed in this research.
- To accurately detect and categorize hair and scalp disorders, the architecture called VGG-DiNAT is used.
- To enhance accuracy and to reduce computational complexity, RCC optimization is employed.

## II.2 PAPER ORGANIZATION

This paper is organized as follows: Section II provides an explanation of the proposed system description. The study methodology is thoroughly described in Section III, which also includes examples of the process, methods, and mathematical representations. The experimental results of this work are described in Section IV, which also include the simulation setup, comparison analysis, and research summary. The conclusion of the proposed investigation is explained in Section V.

## III. PROPOSED SYSTEM DESCRIPTION

The proposed system provides a comprehensive and intelligent image-processing and classification framework intended to produce highly accurate and reliable classification results, in particular when issues arise from low image quality, variability, and limited datasets. The workflow begins with the input dataset, which may contain unwanted noise and visually contradictory patterns which prevent analysis. The diagram of proposed block diagram is depicted in Figure 2.

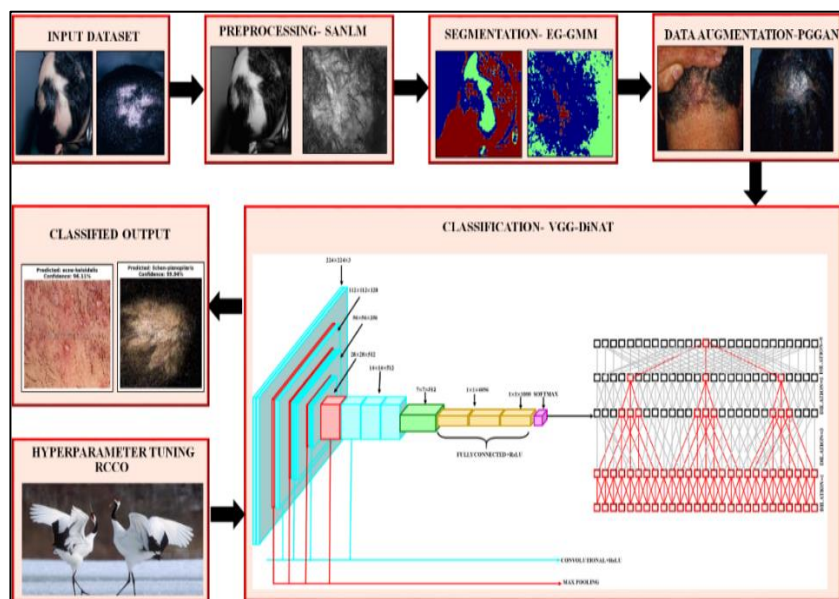


Figure 2: Block diagram of the proposed model.

Source: Authors, (2026).

The system inductees with SANLM preprocessing, which is a sophisticated denoising method that removes the noise while preserving essential edges and texture. The images, having been cleaned, are then segmented with the EG-GMM, which simultaneously application of edge cues in the clustering, allows the system to extract relevant regions of interest. Considering the obstacles when dealing with limited datasets and imbalance, the system includes PGGAN applied to augment the dataset dimensions, generating synthetic realistic high-resolution images, which added data to support good generalization. The images, having been processed and augmented, are then classified with a VGG-DiNAT model, a hybrid network architecture that combines deep feature learning of VGG models, with the attention learning benefits of DiNAT. Additional to generating the classification output, hyperparameter associated with the classifier are optimized in a timely manner expect to improve performance with the RCCO; and the system produces highly accurate and reliable classification output with better performance throughout the entire sequence of procedure.

## IV. PROPOSED SYSTEM MODELLING

### IV.1 PREPROCESSING – SPATIALLY ADAPTIVE NON- LOCAL MEANS

To accurately diagnose hair and scalp conditions while preserving fine anatomical and textural details such as follicular openings, shaft irregularities, perifollicular scaling, and pigmentation patterns, SANLM denoising algorithm is deployed. SANLM replaces each voxel  $x_i$  in a trichoscopic volume  $u$  with a weighted average of intensities in a search region  $v_i$ .

$$NL(u)(x_i) = \sum_{x_j \in v_i} w(x_i, x_j) \cup (x_j) \quad (1)$$

In which case the weights satisfy  $w(x_i, x_j) \in [0,1]$  and  $\sum w(x_i, x_j) = 1$ . It refer to their similarity in local neighborhoods  $N_i$  and  $N_j$

$$w(x_i, x_j) = \frac{1}{Z_i} \exp\left(\frac{-\|u(N_i) - u(N_j)\|^2}{h^2}\right) \quad (2)$$

With  $h^2$  controlling smoothing strength and  $Z_i$  ensuring normalization. Hair and scalp images exhibit strong non-stationary noise due to uneven lighting, dense overlapping hairs, and heterogeneous skin reflectance. Consequently, SANLM does not use a global variance; instead, it develops a local noise estimation that is locally added instead of globally. The expected squared distance between noisy patches is

$$d(N_i, N_j) = E\|u(N_i) - u(N_j)\|^2 = \|u_0(N_i) - (N_j)\|^2 + 2\sigma^2 \quad (3)$$

This is simplified to  $d(N_i, N_j) = 2\sigma^2$  to compare identical patches. However, since identical patches rarely exist in real dermatological data, SANLM computes a residual volume

$$R = u - c(u) \quad (4)$$

Where,  $c(u)$  is a  $3 \times 3 \times 3$  local low-pass filtered version of the image, and this estimation enables the algorithm to set,

$$\sigma^2 = \min_{j \neq i} d(R_i, R_j) \quad (5)$$

$$h^2 = \sigma^2 \quad (6)$$

This process ensures that the denoising strength adapts spatially to the degree of local noise. As a result, SANLM keeps diagnostically useful textures, while denoising the images efficiently, which increases the reliability of automatic classification for disorders of hair and scalp.

### IV.2 SEGMENTATION- EDGE-GUIDED GAUSSIAN MIXTURE MODEL

Gaussian Mixture Models (GMM) is paired with edge guidance to better segment hair and scalp disorders, like alopecia, dandruff, scalp lesions, weakly supervised labels classify pixels. Gaussian Mixture Model created to model distribution of labeled pixels in deep feature space. Mean feature vector  $\mu_i$  for  $i$ -th scalp category represents  $K$  categories: healthy, lesion, follicle.

$$\mu_i = \frac{1}{|x_{li}|} \sum_{x \in x_{li}} f(x) \quad (7)$$

The feature vector for pixel  $x$  is given by  $f(x)$ , which is obtained using a deep feature extraction technique. To generate pseudo-labels for each unlabelled pixel  $x_u$ , the distance  $d_i$  of that pixel to the  $i$ -th Gaussian component is calculated based on the difference between the feature vectors,

$$d_i = \frac{1}{|c|} (f(x_u) - \mu_i)^2 \quad (8)$$

In this equation,  $C$  represents the total number of channels in the feature space. After calculating the distances, assign pseudo-labels to each unlabelled pixel according to the category represented by the nearest Gaussian component, which is denoted by the smallest distance.

$$G(x_u) = \sum_i e^{-d_i^2} \quad (9)$$

For every iteration, of the previously labeled pixels and add new pixels to them if their probability is above a predetermined level based on our model's predictions, storing them within an information mask  $M$  for each iteration. During this iterative approach, the number of pixels in our masks will continue to increase, which in turn will produce fewer errors and noise concerning our segmentations by building a larger dataset from all labeled pixels throughout each iteration. Moreover, to enhance the detection of boundaries, which are significant for the precise diagnosis of hair and scalp issues, present an RGB-Edge Fusion module that uses edge guidance. The module incorporates edge feature maps into RGB feature maps, which facilitates the model to correctly separate complex areas, such as the border of the hairline, and scalp lesions. The process of fusing edge and RGB features is defined as:

$$f_{re} = GAP\left(conv^{3 \times 3}\left(cat(f_{rgb}, f_{edge})\right)\right) \quad (10)$$

Conv is an operation of  $3 \times 3$  convolution, cat refers to concatenation, and GAP is the abbreviation of Global Average Pooling. The features fused together will then flow into a Spatial Attention Mechanism, which will allow for the most relevant feature sets to be used when segmenting. To make this happen, the output Fused Feature Vector  $F_u$  is generated from the concatenated and pooled data as follows:

$$f_u = \text{cat} \left( \text{conv}^{1*1}(f_{re}), \text{conv}^{1*1}(f_{rgb}) \right) \quad (11)$$

The model is created with a loss function that takes into account all losses, including self-supervised losses  $L_i$ , weakly-supervised losses  $L_v$ , Contrast Losses  $L_c$ , and Fusion Losses  $L_f$ . Thus, the complete loss will be calculated as:

$$L_{total} = L_{self} + L_{weak} + L_{con} + L_{fusion} \quad (12)$$

This loss function facilitates the learning of accurate pixel-level labels by guiding the boundary detection process, which is essential for identifying different regions such as, hair follicles, scalp lesions, and areas of healthy scalp.

#### IV.3 DATA AUGMENTATION- PROGRESSIVE GROWING GAN

Exploiting hair diagnosis and scalp disorders using PG-GAN learns to organize and present the image structure in both stable and incremental. Initially, training begins on a very low-resolution ( $4 \times 4$ ) where the generator capture the larger structure of scalp characteristics. While training, additional layers are added to the Generator and Discriminator until reaching the highest resolution of  $1024 \times 1024$  which allow the model to learn about smaller Clinical detail such as scaling edges, follicular openings, erythema, lesion contours. The incremental style of approach provides for stability in adversarial learning and helps reduce the computational burden on the systems as a result of the fact that most of the training iterations happen at smaller resolution images, before transitioning into larger resolution images with their full detail. In addition, the approach provides for generating highly realistic and diverse images of scalp images and captures the finer textures and complex interactions between hair and skin that are so important for the Dermatological evaluation process. Once the generator has been trained to generate images at the highest available resolution, it produce images to support data augmentation, super-resolution enhancement of trichoscopy images, and domain adaptation between different imaging environments, thus creating strong automated systems for consistently and accurately diagnosing hair and scalp disorders.

#### IV.4 CLASSIFICATION- VGG-DINAT

In diagnosing scalp and hair problems, the deep Convolutional Neural Network (CNN) known as VGG-19 has many potential uses for trichoscopic imaging such as identifying a variety of scalp and hair conditions. The 19-layer architecture of VGG-19 is comprised of 16 convolutional layers that extract features and 3 fully connected layers that provide classification. The convolutional parts of VGG-19 identify many types of features, including follicular openings, scalp texture, and hair distribution. The final fully connected layers then classify each previously extracted feature as being part of either a normal or diseased scalp. By using the max-pooling layers to reduce dimensionality, VGG-19 prevents the overfitting problem and promotes generalization. The equations used to calculate the output from the convolutional layers can be defined in the following manner,

$$C_j^l = \varphi \left( \sum_{i=1}^{M^{l-1}} C_i^{l-1} \times k_{ij}^l + b_j^{l-1} \right) \quad (13)$$

For  $C_j^l$  which is the output feature of the  $j$ -th filter from the  $l$ -th layer,  $\varphi(x)$  represents an activation function (usually ReLU),  $k_{ij}^l$  is the convolution kernel, and  $b_j^{l-1}$  is the bias term. After calculating the outputs of all filters in a given layer, the next step is to use a max-pooling layer to reduce the dimensions of the resulting feature maps. Finally, the final layer of VGG-19 uses the features extracted from prior steps and classifies each feature using a softmax function to determine whether or not they belong to each of the conditions identified by VGG-19. Using a layered neural net structure in combination with functions such as ReLU and dropout layers allows for training with identified images that illustrate conditions affecting both hair and scalp and learning detailed characteristics from layers of the network. The automated classification of images in this way gives dermatologists a useful tool for diagnosing patients' hair and skin problems based on photographic evidence. The DiNAT has the potential to accurately perform diagnoses on scalp and hair disorders with its unique ability to be able to take into account both long distance spatial relationships and local distinct features of images. The DiNAT architecture would then process as input the token vector representation of the input images of the scalp and hair, and then use the DiNAT architecture to locate similar patterns found in scalp and hair disorder based on alopecia, seborrheic dermatitis, and psoriasis. Enchanting an input image  $X \in R^{n \times d}$  is the number of image patch and will determine the dimension of the feature vector for every image. Through calculating the attention weights based upon the neighborhood tokens, DiNAT identifies the corresponding images associated with the scalp area by grouping and linking the images depending on their spatial proximity to one another, helping the model capture the relationship between the images, helping to locate key of importance to the diagnosis process. The structure of VGG-DiNAT is illustrated in Figure 3.

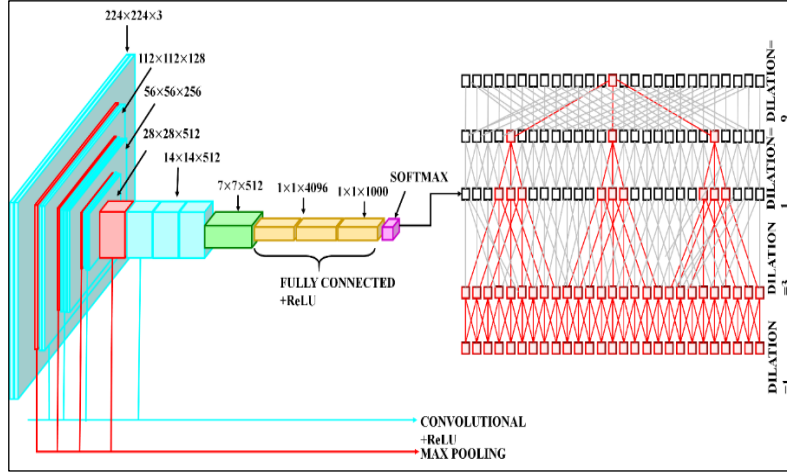


Figure 3: Architecture of VGG-DiNAT.

Source: Authors, (2026).

Attention weights  $A_i^k$  for a given image  $i$  are calculated by multiplying the token's corresponding  $Q_i$  query projection with the image corresponding to  $k$ . In DiNAT, the dilation factor  $\delta$  is then able to model long range dependencies in the form of neighbours which is chosen according to the dilated neighbor pattern. Each dilated neighbor  $\rho_j^\delta(i)$  means the  $j^{th}$  nearest neighbour of the  $i^{th}$  token based on the condition  $j \bmod(\delta) = i \bmod(\delta)$ . Thus, each dilated attention weight  $A_{i,k,\delta}^i$  be determined just like the original attention weights, just by applying the dilated neighbor patterns when selecting the dilated neighbours.

$$A_i^{(k,\delta)} = \begin{bmatrix} Q_i K_{\rho_1^\delta(i)}^T + B(i, \rho_1^\delta(i)) \\ Q_i K_{\rho_2^\delta(i)}^T + B(i, \rho_2^\delta(i)) \\ \vdots \\ Q_i K_{\rho_k^\delta(i)}^T + B(i, \rho_k^\delta(i)) \end{bmatrix} \quad (14)$$

The dilated neighbouring values  $V_i^{(k,\delta)}$  are calculated in the same way, later on, as they were computed above; however in this case, these dilated neighbouring values are inputted into DiNAT at the end of the process.

$$V_i^{(k,\delta)} = \begin{bmatrix} V_{\rho_1^\delta(i)}^T & V_{\rho_2^\delta(i)}^T & \dots & V_{\rho_k^\delta(i)}^T \end{bmatrix}^T \quad (15)$$

The DiNAT output for token  $i$  with neighbourhood size  $k$  and dilation factor  $\delta$ . This method provides information about the dilated neighbours by capturing their local & long-range connections via their dilated neighbouring pixels, which are important for recognising & diagnosing scalp disorders.

$$DiNAT_K^\delta(i) = softmax\left(\frac{A_i^{(k,\delta)}}{\sqrt{d_k}}\right) V_i^{(k,\delta)} \quad (16)$$

By combining VGG-19 and DiNAT, which is used to properly diagnose scalp disorder conditions. The VGG-19 architecture allows for elaborate, deep feature extraction & enables to use the DiNAT attention mechanism to build a model that decodes both local & large-scale patterns in order to effectively diagnose hair and scalp disorders. This hybrid approach allows for high levels of recognition along accomplishment with automated health assessments of scalp images.

#### IV.5 RED-CROWNED CRANE OPTIMIZATION

The RCCO algorithm employs the behaviors of Red-Crowned Cranes such as foraging, avoiding danger, and roosting. In Hair and scalp disorders such as alopecia, psoriasis, and seborrheic dermatitis, the classification is optimised using RCCO, where a group of candidate solutions (Cranes) is generated randomly within the search space and represented as potential diagnostic models and iterated to find the optimal classification model. Each crane's position  $X_i$  is a possible solution in the search space, and its fitness  $F(X)$  is calculated by the objective function, which directs the search towards finding the most precise and best model. The population is divided into random foragers, which search near the best solution and long-distance foragers which explore further away from the best solution. Random foragers adjust their positions based on the best solution they have found, while long-distance foragers move further. This dynamic is analogous to exploring many different types of hair and Scalp Images.

Table 1: Optimized values of RCCO.

| Parameter | Meaning                                                               | Value |
|-----------|-----------------------------------------------------------------------|-------|
| pop_size  | Number of cranes (population size)                                    | 10    |
| max_iter  | Number of optimization iterations (how many times population evolves) | 10    |

| Parameter          | Description                                       | Search Range |
|--------------------|---------------------------------------------------|--------------|
| Learning Rate (lr) | Step size for Adam optimizer                      | [1e-5, 1e-3] |
| Dropout            | Regularization strength in dense layers           | [0.2, 0.5]   |
| Filters            | Embedding dimension or number of feature channels | [16, 48]     |

Source: Authors, (2026).

The second aspect of the crane's life cycle is roosting, the behavior of cranes gathering together in a new location, is indicative of cranes learn from each other's experiences and the convergence of solutions move them to the optimal location. Mathematically, the position update for gathering is indicated by,

$$X_i(t+1) = X_i^0(t+1)C_3 \cdot r_3 \cdot (X_{home}^0(t+1)) - (X_i^0(t+1)) \quad (17)$$

Where,  $X_{home}^0(t+1)$  is the updated habitat  $C_3$  is the time varying coefficient and  $r_3$  is the random factor, directing the cranes towards the best location discovered. The dance of cranes is the interaction of the top two fitness values, the best and second best further refining their location and behavior through interaction, similar to two paired cranes move together synchronously in flight. This is indicated by,

$$X'_i(t+1) = X_i(t) + u \cdot (r_4 \cdot X_{first}(t) - X_i(t)) \quad (18)$$

$$X''_i(t+1) = X_i(t) + u \cdot (r_4 \cdot X_{second}(t) - X_i(t)) \quad (19)$$

The value for  $u$  is selected at random from a Gaussian distribution,  $r_4$  is a deviation coefficient,  $X_{first}(t)$  and  $X_{second}(t)$  are the first two solutions. Evaluation of the fitness of a solution is key to steering the search towards finding the best possible diagnostic model, which is progressively being developed through these behaviours. The flowchart of VGG-DINAT WITH RCCO is depicted in Figure 4.

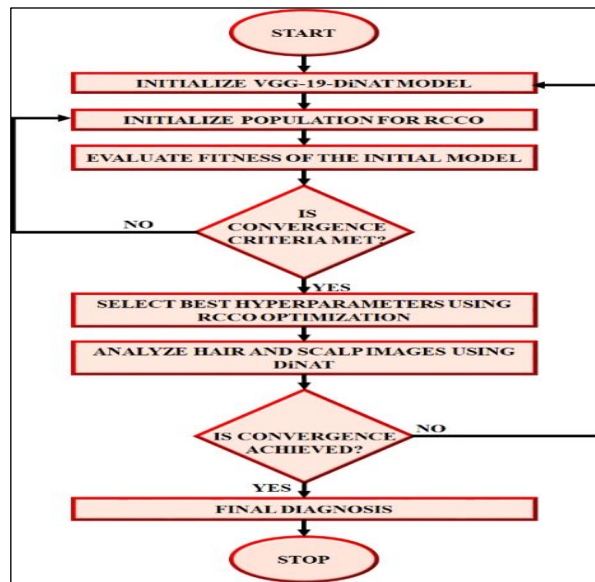


Figure 4: Flowchart of VGG-DINAT WITH RCCO.

Source: Authors, (2026).

The nature of the computational complexity allows for effective searching and refining of the solutions during the optimization phase. Finally, RCCO assist in identifying the best possible diagnostic models for diagnosing hair and scalp disorders by combining techniques of exploration, exploitation and convergence based on the natural behaviours of red-crowned cranes. The output provide information on all scalp disease and hair disease, such as alopecia and seborrheic dermatitis. Combining the deep feature extraction of VGG-19, the attention mechanism of DiNAT, and the Optimization of RCCO provides an extremely effective and flexible method to solve this diagnostic task.

## V. RESULT AND DISCUSSION

The proposed system makes use of an extensive Hair and Scalp Disease Dataset consisting of different clinical images portraying 14 distinct classes of hair and scalp diseases. The dataset incorporates several pathways with unique visual presentation differences, enabling the framework to learn fine-grained textural features as well scalp abnormalities at a broader level. Its diversity promotes effective model training for both segmentation and classification tasks. Within the dual-stream VGG-DiNAT architecture proposed in this paper, its wealth of data allows features to be learned from both local textural features and global scalp patterns. RCCO also helps to enhance classification accuracy by fully optimizing hyperparameter for each of the disease categories separately.

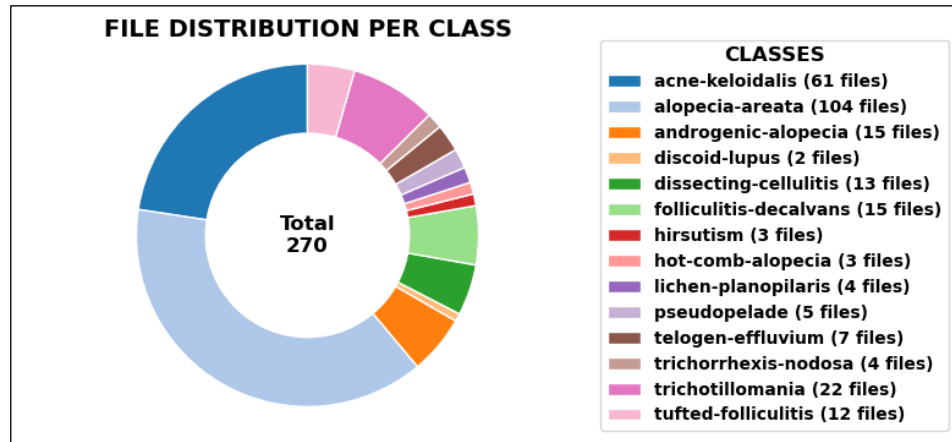


Figure 5: File distribution per class.

Source: Authors, (2026).

Figure 5 indicates that alopecia-areata and acne-keloidalis constitute the bulk of 270 total files, while most other scalp conditions exhibit a low number of files, and therefore an imbalanced class distribution.

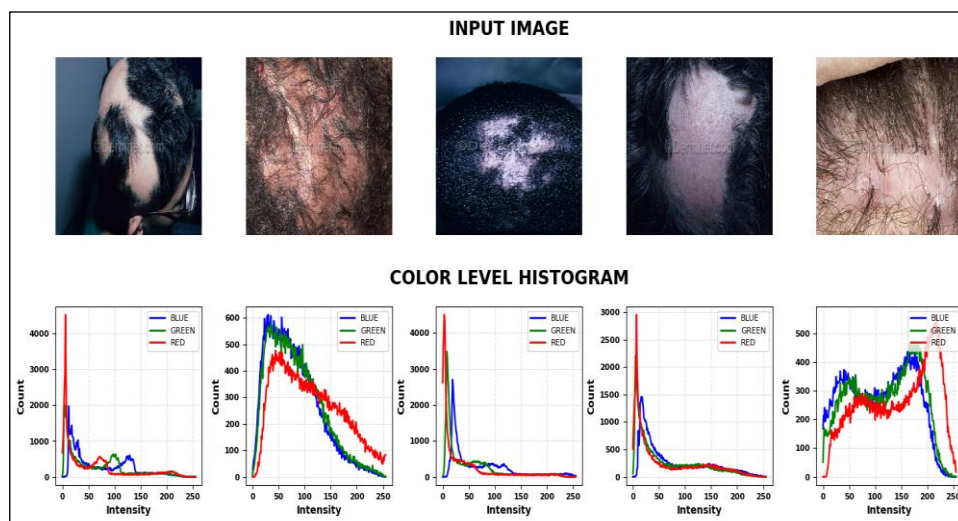


Figure 6: Input image with color level histogram.

Source: Authors, (2026).

Figure 6 displays several scalp images with the corresponding color-level histograms underneath the images. The histograms present the distribution of red, green, and blue image intensities to illustrate variations of brightness and color across each image - some images are more heavily black vs. red while other images appear with the wider range of intensity being balanced among the three colors.

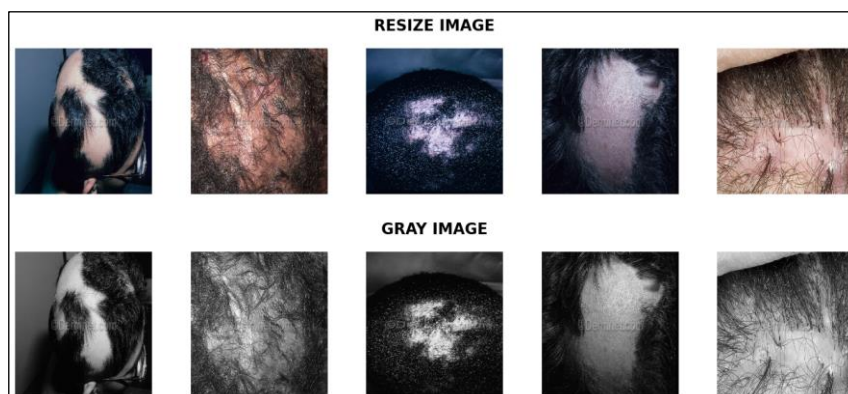


Figure 7: Resize image with gray image.

Source: Authors, (2026).

Figure 7 depicts a set of scalp images after a resizing process along with grayscale images corresponding to each image. Each grayscale version pairs with its color image to show the variation of texture and structure after the colors are removed, thereby making visual patterns more identifiable.

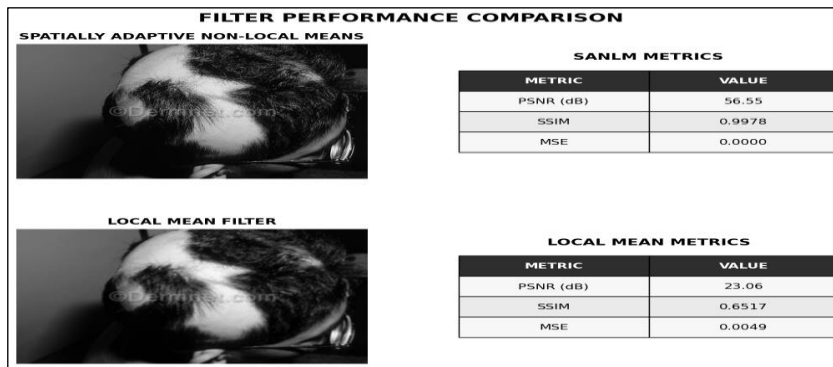


Figure 8: Filter performance comparison.  
Source: Authors, (2026).

Figure 8 gives a direct comparison between two denoising filters that were applied to the same scalp photograph. The Spatially Adaptive Non-Local Means (SANLM) filter outputs a much clearer and clearer image with a very high PSNR (56.55 dB) which is much more than perfect SSIM (0.9978) and it has a 0 for MSE. The output of the Local Mean Filter is noticeably blurry with a significantly lower PSNR (23.06 dB) and a lower SSIM (0.6517) with a higher MSE. Overall, the image illustrates that detail and accuracy is conserved with the SANLM.

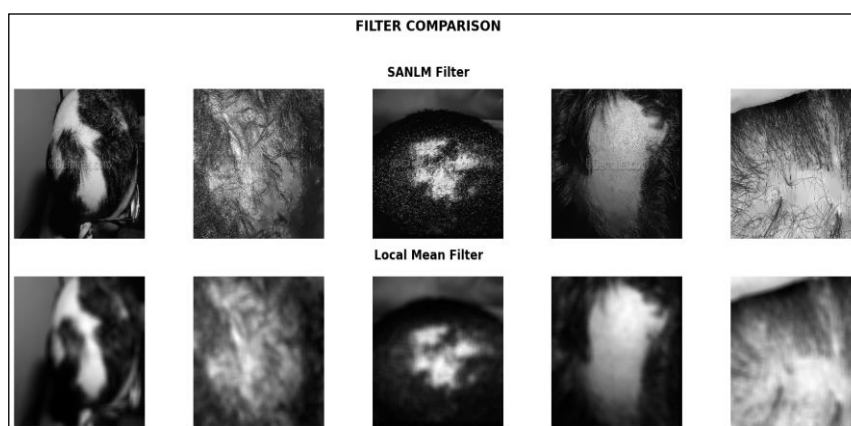


Figure 9: Filter comparison.  
Source: Authors, (2026).

Figure 9 displays side-by-side visual comparisons of two different filtering approaches in scalp images taken at close-up view. The upper row shows outputs produced by the SANLM filter, which maintains fine hair detail, texture, and edge detail much better from the original visuals. The lower row shows the same images processed by the Local Mean Filter, which is noticeably blurrier and loses structural detail in the images. Ultimately, the comparison emphasizes the SANLM filter's much better ability to maintain sharpness and a natural texture while performing denoising.

| METRIC COMPARISON |        |            |          |        |            |          |        |            |
|-------------------|--------|------------|----------|--------|------------|----------|--------|------------|
| IMAGE 1           |        |            | IMAGE 2  |        |            | IMAGE 3  |        |            |
| Metric            | SANLM  | Local Mean | Metric   | SANLM  | Local Mean | Metric   | SANLM  | Local Mean |
| PSNR(dB)          | 50.24  | 22.34      | PSNR(dB) | 34.00  | 18.25      | PSNR(dB) | 41.45  | 19.74      |
| SSIM              | 0.9910 | 0.5982     | SSIM     | 0.9359 | 0.1419     | SSIM     | 0.9565 | 0.3584     |
| MSE               | 0.0000 | 0.0058     | MSE      | 0.0004 | 0.0150     | MSE      | 0.0001 | 0.0106     |
| IMAGE 4           |        |            | IMAGE 5  |        |            |          |        |            |
| Metric            | SANLM  | Local Mean | Metric   | SANLM  | Local Mean |          |        |            |
| PSNR(dB)          | 39.60  | 23.07      | PSNR(dB) | 40.13  | 17.48      |          |        |            |
| SSIM              | 0.9480 | 0.3361     | SSIM     | 0.9720 | 0.1671     |          |        |            |
| MSE               | 0.0001 | 0.0049     | MSE      | 0.0001 | 0.0179     |          |        |            |

Figure 10: Comparison metrics.  
Source: Authors, (2026).

Figure 10 shows a row of metric tables comparing the output of the SANLM filter performance as compared to the Local Mean filter in each of several test cases. In every table, the SANLM filter achieved far higher PSNR and SSIM values, as well as a dramatically lower MSE, meaning it kept much better image quality and structural detail. In contrast, the Local Mean filter performed poorly, with lower clarity and more reconstruction error.

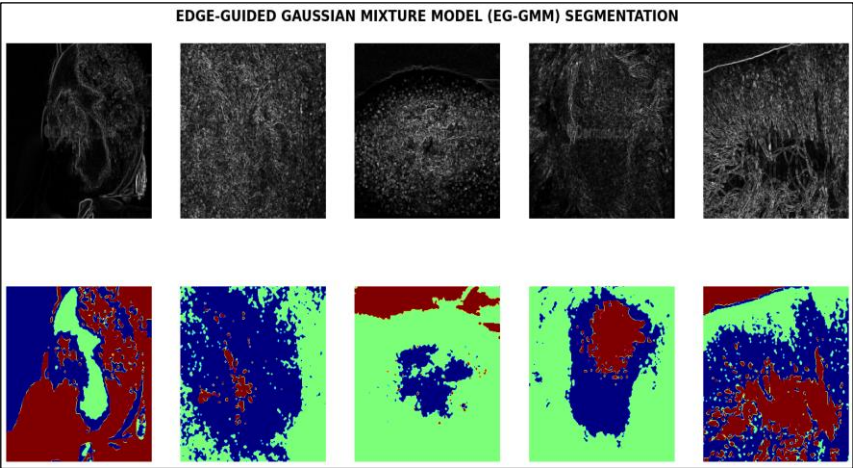


Figure 11: EG-GMM segmentation model.  
Source: Authors, (2026).

Figure 11 shows original grayscale structural images on the upper row and the EG-GMM color-coded segmentation results of each image on the lower, with separate areas indicated by edginess and differing intensities.

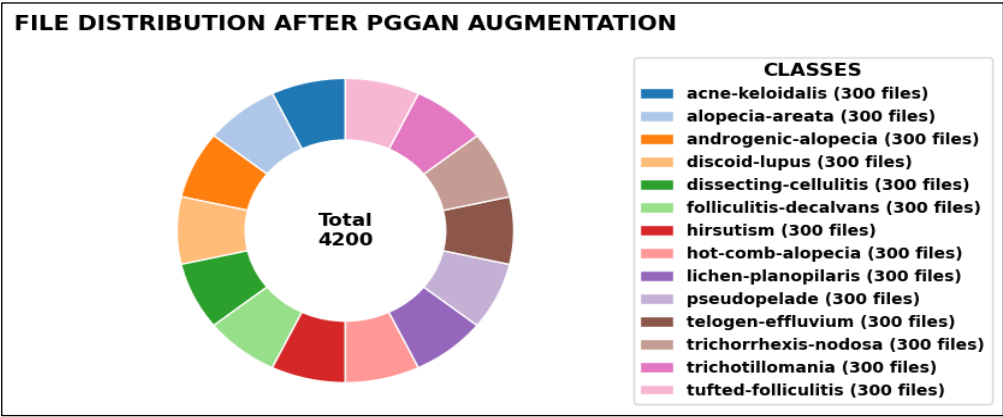


Figure 12: File distribution after PGGAN augmentation.  
Source: Authors, (2026).

Figure 12 displays a donut graph illustrating the sample distribution after the PGGAN augmentation process, for a total of 4200 samples. Each of the 14 medical imaging classes has 300 augmented samples, which are categorized in a unique, colored section around the donut chart. On the right, there is a legend to describe the full list of classes. In summary, after the process of augmentation, there is a balanced dataset of varied medical imaging classes.

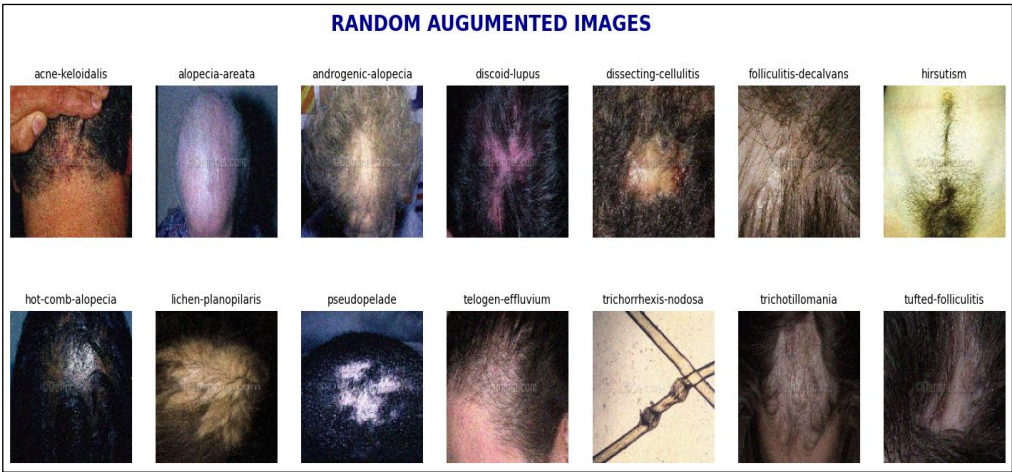


Figure 13: Random augmented images.  
Source: Authors, (2026).

Figure 13 shows the set of randomly selected images of augmented scalp and hair conditions, with the corresponding class label. The images depict a variety of textures, colors, and patterns, produced through augmentation, depicting the visual diversity of such hair- or scalp-related conditions for instance, alopecia, folliculitis, dermatitis, and other scalp and hair conditions.

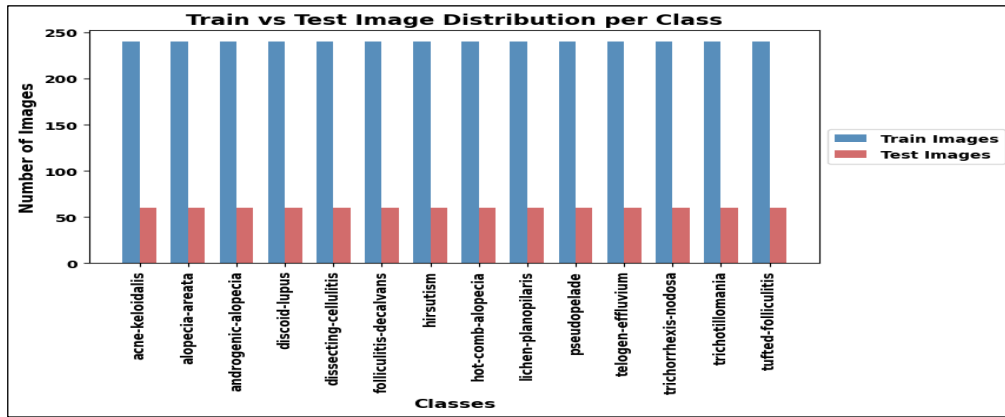


Figure 14: Train vs Test image distribution per class.  
Source: Authors, (2026).

Figure 14 illustrates the number of training and test images across the hair- and scalp-related conditions in the dataset. All classes depict a balanced distribution with approximately 240 training images and about 60 test images per augmented class. Each of the medical imaging classes such as acne-keloidalis, alopecia-areata, trichotillomania, and tufted-folliculitis are evenly-distributed and well-balanced across the dataset.

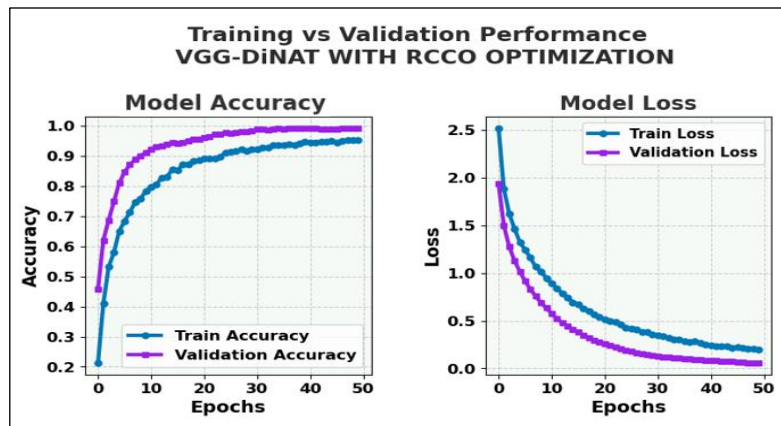


Figure 15: Training vs validation performance of VGG-DiNAT with RCCO.  
Source: Authors, (2026).

Figure 15 indicates steadily improving accuracy, and a decreasing loss with training and validation. Throughout the training, the validation performance is slightly higher, indicating that the model is learning to generalize without any excessive overfitting.

Table 2: Classification metrics of VGG- DiNAT with RCCO.

| METRICS            | SCORE  |
|--------------------|--------|
| Accuracy           | 0.9929 |
| Macro Precision    | 0.9929 |
| Macro Recall       | 0.9929 |
| Macro FI-Score     | 0.9929 |
| Weighted Precision | 0.9929 |
| Weighted Recall    | 0.9929 |
| Weighted FI-Score  | 0.9929 |
| Balanced Accuracy  | 0.9929 |
| Cohen's Kappa      | 0.9923 |
| Matthews CorrCoef  | 0.9923 |

Source: Authors, (2026).

Table 2 shows the VGG-DiNAT model with RCCO which demonstrates remarkable performance, attaining 0.9929 across accuracy, precision, recall, F1-score, and balanced accuracy - this score indicates that the model can classify the three classes in a highly reliable and consistent manner. Furthermore, Cohen's Kappa and MCC were also 0.9923, further demonstrating the model's agreement and recounting other capability positively predicts class membership, showing strong robustness.

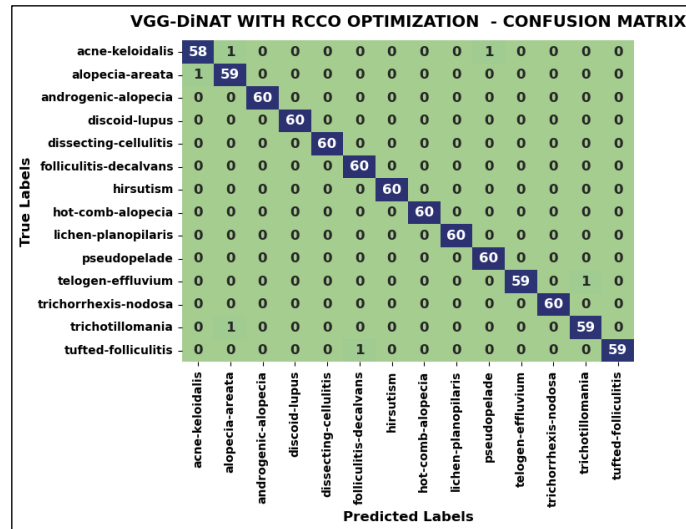


Figure 16: Confusion matrix of VGG-DiNAT with RCC optimization.  
Source: Authors, (2026).

Figure 16 presents the confusion matrix for a model VGG-DiNAT with RCCO Optimization. The confusion matrix explains the accuracy of the model differentiating the different classes, in this case, hair loss or scalp conditions. The diagonal values highlight the number of correct predictions for each of the classes, and most of the classes in the diagonal have a value of 60. These values indicate that the model is performing as anticipated, as the vast majority of predictions match the true labels. The green and blue colors help identify these predicted true positive values.

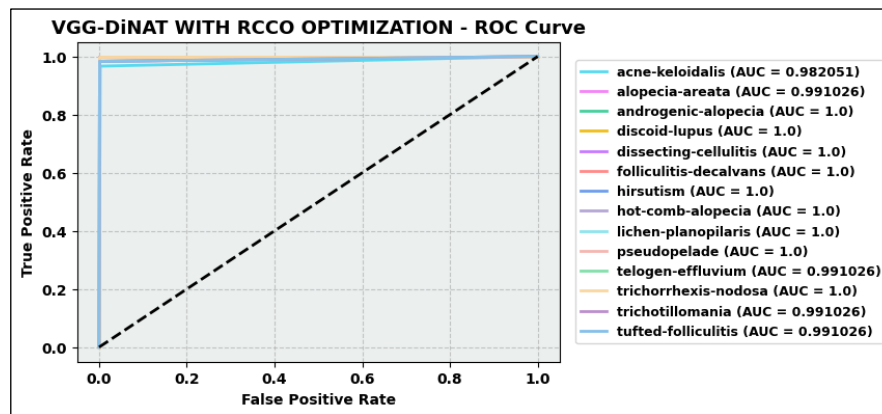


Figure 17: ROC curve of VGG-DiNAT with RCC optimization.  
Source: Authors, (2026).

Figure 17 shows the ROC curve for VGG-DiNAT with RCCO Optimization model. The ROC curve has different lines for each class, and the AUC values are displayed for each class also. Most classes have an AUC of 1.0 indicating a perfect classification and only the acne-keloidalis class has an AUC of 0.982 showing it to be slightly below perfect classification. The curve is situated closely to the top left corner, indicating that the model has high accuracy and low false positives.

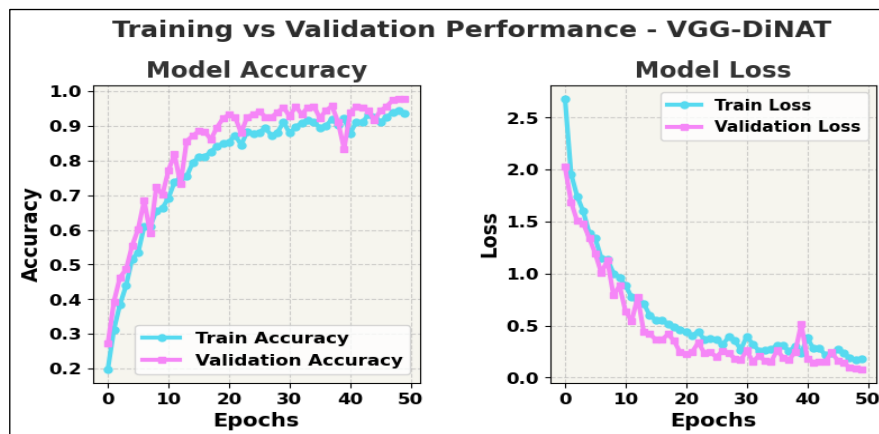


Figure 18: Training vs Validation performance of VGG-DiNAT.  
Source: Authors, (2026).

Figure 18 depicts the training and validation performance of the VGG-DiNAT model for 50 epochs. The accuracy plot indicates a gradual increase in training and validation accuracy, ultimately exceeding 0.9, suggesting that the model was learning aggressively and generalizing well. The loss plot shows a steady decrease in both training and validation loss, and they align closely, indicating no overfitting and the model is stable across training and validation sets.

Table 3: Classification metrics of VGG- DiNAT model.

| METRICS            | SCORE  |
|--------------------|--------|
| Accuracy           | 0.9774 |
| Macro Precision    | 0.9776 |
| Macro Recall       | 0.9774 |
| Macro F1-Score     | 0.9772 |
| Weighted Precision | 0.9776 |
| Weighted Recall    | 0.9774 |
| Weighted F1-Score  | 0.9772 |
| Balanced Accuracy  | 0.9774 |
| Cohen's Kappa      | 0.9756 |
| Matthews CorrCoef  | 0.9757 |

Source: Authors, (2026).

Table 3 shows the VGG-DiNAT model that produced consistent classification performance characterized by accuracy, precision, recall, and F1-scores, each averaging around 0.977. The macro and weighted averages indicate equally good performance across classes, suggesting that predictions are reasonably balanced. The value obtained for the Cohen's Kappa (0.9756) and Matthews Correlation Coefficient (0.9757) indicates strong agreement with true labels, thus suggesting that the model is reliable and robust.

**VGG-DiNAT MODEL - Confusion Matrix**

|                        |    |    |    |    |    |    |    |    |    |    |    |    |    |   |    |
|------------------------|----|----|----|----|----|----|----|----|----|----|----|----|----|---|----|
| acne-keloidalis        | 53 | 2  | 0  | 0  | 3  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0 | 2  |
| alopecia-areata        | 0  | 56 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 3 | 1  |
| androgenic-alopecia    | 0  | 0  | 60 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0 | 0  |
| discoid-lupus          | 0  | 0  | 0  | 60 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0 | 0  |
| dissecting-cellulitis  | 0  | 0  | 0  | 0  | 60 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0 | 0  |
| folliculitis-decalvans | 1  | 0  | 0  | 0  | 0  | 58 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0 | 1  |
| hirsutism              | 0  | 0  | 0  | 0  | 0  | 0  | 60 | 0  | 0  | 0  | 0  | 0  | 0  | 0 | 0  |
| hot-comb-alopecia      | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 60 | 0  | 0  | 0  | 0  | 0  | 0 | 0  |
| lichen-planopilaris    | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 60 | 0  | 0  | 0  | 0  | 0 | 0  |
| pseudopelade           | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 60 | 0  | 0  | 0  | 0 | 0  |
| telogen-effluvium      | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 60 | 0  | 0  | 0 | 0  |
| trichorrhexis-nodosa   | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 60 | 0  | 0 | 0  |
| trichotillomania       | 2  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 55 | 2 | 0  |
| tufted-folliculitis    | 0  | 0  | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0 | 59 |

**Predicted Labels**

Figure 19: Confusion matrix of VGG-DiNAT model.

Source: Authors, (2026).

Figure 19 illustrates the confusion matrix that indicates the performance of the VGG-DiNAT model to classify the hair and scalp conditions. The model exhibited better performance, as most predictions lie along the diagonal, there were instances of misclassification, specifically androgenic-alopecia predicted as acne-keloidalis. Overall, the model indicates a high level of accuracy for skin condition prediction.

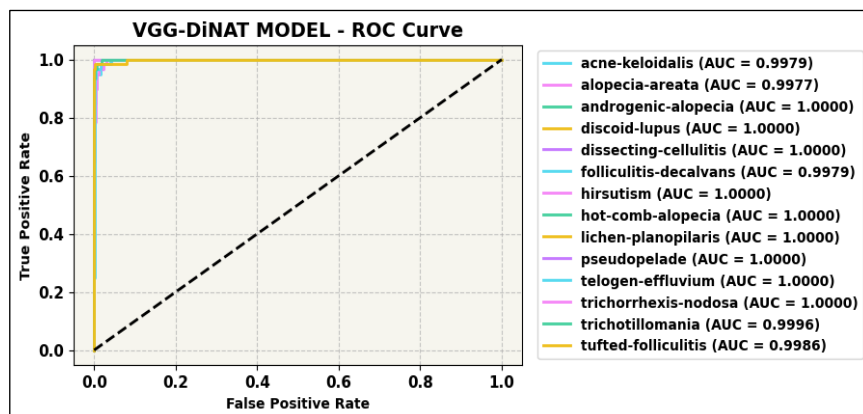


Figure 20: ROC curve of VGG-DiNAT model.

Source: Authors, (2026).

Figure 20 provides a summary of the ROC curve for a VGG-DiNAT model used to classify different hair and scalp conditions. All classes have very high AUC scores, indicating excellent performance in the classification of hair and scalp conditions across all circumstances.

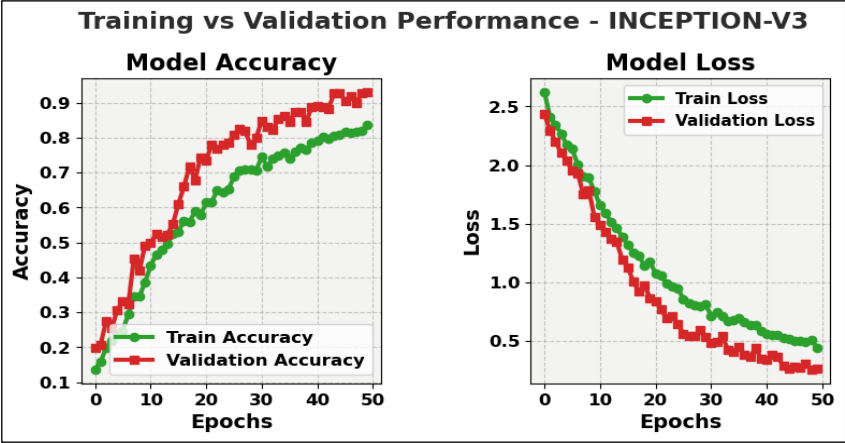


Figure 21: Training vs validation performance of Inception V3.  
Source: Authors, (2026).

Figure 21 detail the training and validation of performance of an Inception-V3 model across 50 epochs. Both the accuracy curves trend upwards, and validation accuracy stays consistently above training accuracy, reaching above 0.9. The loss curves for training and validation are both declining at a smooth rate, with validation loss staying slightly below training loss throughout the epochs.

Table 4: Classification metrics of Inception V3 model.

| METRICS            | SCORE  |
|--------------------|--------|
| Accuracy           | 0.9310 |
| Macro Precision    | 0.9322 |
| Macro Recall       | 0.9310 |
| Macro FI-Score     | 0.9300 |
| Weighted Precision | 0.9322 |
| Weighted Recall    | 0.9310 |
| Weighted FI-Score  | 0.9300 |
| Balanced Accuracy  | 0.9310 |
| Cohen's Kappa      | 0.9256 |
| Matthews CorrCoef  | 0.9259 |

Source: Authors, (2026).

Table 4 model shows strong and steady performance of approximately 93% accuracy, with comparable precision, recall, and F1-scores. The elevated Cohen's Kappa and Matthews Correlation Coefficient indicate reliability and a well-balanced range of the predictions across classes.

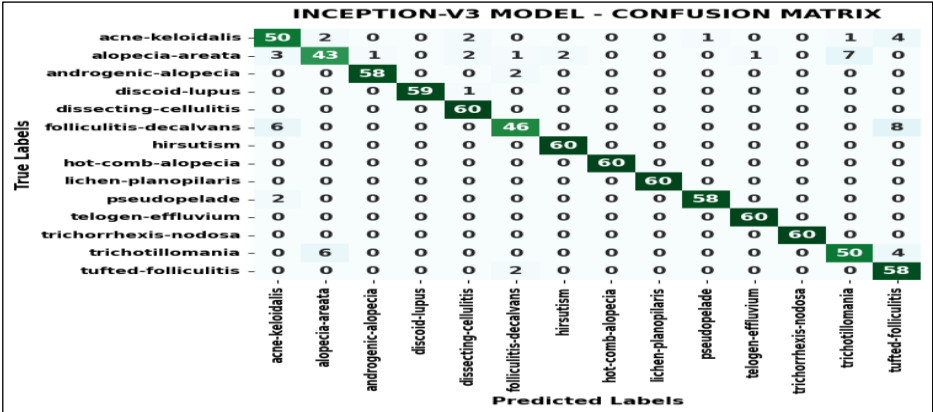


Figure 22: Confusion matrix of Inception V3 model.  
Source: Authors, (2026).

Figure 22 shows the confusion matrix which illustrates that the Inception-V3 model is able to correctly classify the majority of samples in all categories, with clustered diagonals suggesting strong levels of accuracy. Only a small portion of misclassified categories appear across visually similar conditions, but overall, the confusion matrices suggests that the performance across classes are reliable and consistent.

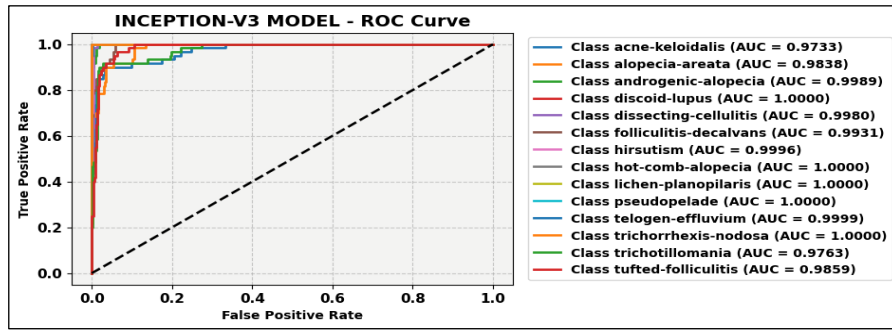


Figure 23: ROC curve of Inception V3 model.

Source: Authors, (2026).

In Figure 23, the model demonstrates excellent discriminative performance across classes, as indicated by near-perfect values across AUC and ROC curves clustered near the top-left corner of the examination.

Table 5: Classification metrics of proposed and existing model.

| Model        | Accuracy | Precision | Recall | F1-Score |
|--------------|----------|-----------|--------|----------|
| PROPOSED     | 0.9929   | 0.9929    | 0.9929 | 0.9929   |
| VGG-DiNAT    | 0.9774   | 0.9776    | 0.9774 | 0.9772   |
| Inception V3 | 0.931    | 0.9322    | 0.931  | 0.931    |

Source: Authors, (2026).

Table 5 provides a comparison of the three models' classification metrics. The PROPOSED model has achieved the highest rating of 99.3% across all metrics. The VGG-DiNAT model is rated next at 97.7%, and the Inception-V3 model showed the worst performance with 93% accuracy, precision, recall, and F1-score.

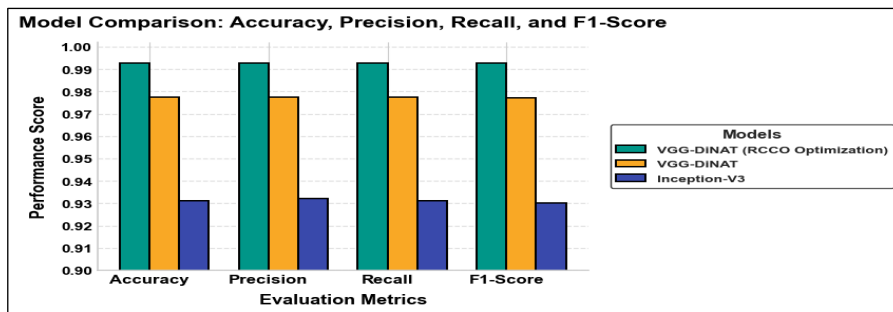


Figure 24: Comparison of evaluation metrics.

Source: Authors, (2026).

Figure 24 provides a comparison of three models using the different metrics of accuracy, precision, recall, and F1-score. The VGG-DiNAT (RCCO Optimization) model performs the best, with scores just under 0.99. The standard VGG-DiNAT model performs next highest, with scores between 0.97 and 0.98, and the Inception-V3 model showed lowest performance around 0.93 for the three models.

Table 6: Comparative analysis of accuracy for various models.

| Model         | Accuracy |
|---------------|----------|
| CNN [22]      | 0.911    |
| ViT-B/16 [23] | 0.823    |
| ANN [24]      | 0.964    |
| HDM-Net [25]  | 0.948    |
| VGG-16 [26]   | 0.945    |
| Proposed      | 0.9929   |

Source: Authors, (2026).

In Table 6, the proposed model, achieves a maximum accuracy of 0.9929, higher than other models such as CNN (0.911), ViT (0.823) and VGG-16 (0.945) for diagnosing hair and scalp diseases. In the proposed system CNN is used to verify the accurate model of the proposed system which is used in the system to transfer the details from the given table

Table 7: Comparative analysis of precision for various methods.

| Model         | Precision |
|---------------|-----------|
| CNN [22]      | 0.895     |
| ViT-B/16 [23] | 0.831     |
| ANN [24]      | 0.983     |
| Proposed      | 0.992     |

Source: Authors, (2026).

In table 7 there are several models expected to yield different results based on their performance measure. A CNN has a Precision rating of 0.895, ViT-B/16 has a Precision of 0.831, and ANN has achieved a model precision of 0.983. The model developed by the Author in this study has the highest level of accuracy for identifying the True Positive class based upon its Precision score of 0.992.

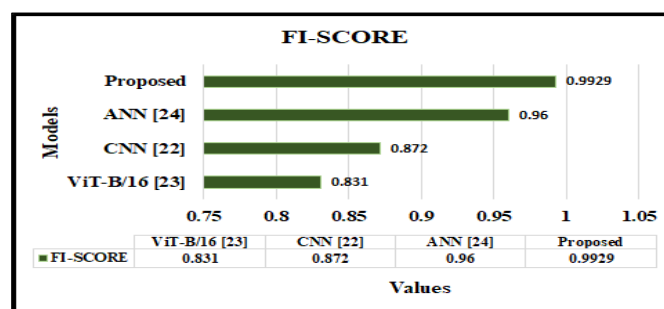


Figure 25: Comparison of FI-score for various methods.  
Source: Authors, (2026).

A bar graph comparing the FI-SCORE value of four different machine learning (ViT-B/16, CNN, ANN, and a proposed) shown in Figure 25. The proposed model had a higher FI-SCORE than the others with an FI-SCORE of 0.9929. The second highest FI-SCORE was obtained by the ANN model with a value of 0.96 while CNN and ViT-B/16 both achieved lower FI-SCORE values at 0.872 and 0.831 respectively.

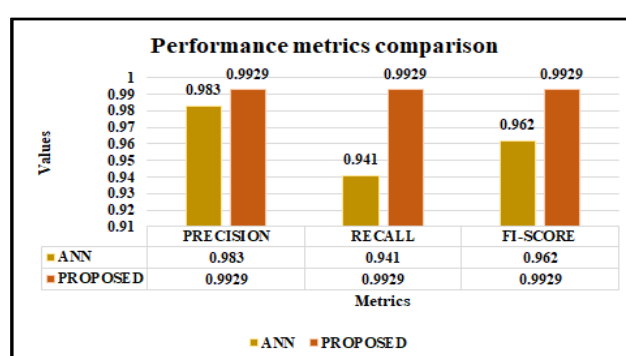


Figure 26: Comparative analysis of proposed and existing methods.  
Source: Authors, (2026).

Compared to the ANN, the proposed model has superior performance across all metrics of measurement which is illustrated in Figure 26. In addition, the Proposed Model's Precision (99.29%) and F-1 Score (99.29%) both outperform the ANN (98.3% Precision and 96.2% F-1 Score), while they have equal Recall (94.1 % Recall).

## VI. CONCLUSION

The proposed approach enhance both the accuracy and speed with which users classify the input images. To accomplish this, the process involves a number of clearly defined phases. The first phase in this process will be an input dataset of raw images that require processing. The first stage of the process is accomplished using a SANLM approach, which provides significant denoising and enhancement of image quality to prepare the data for further analysis. The next step involves segmenting the images into identifiable regions using EG-GMMs. The third stage of the process is data augmentation, involves using a PGGAN to create additional training data for the model in order to expand the size of the dataset and improve robustness through reducing overfitting. The fourth step of the process will utilize a VGG-DiNAT architecture based DL model for the classification of the images based upon extract features. The performance of the model will be enhanced through hyperparameter tuning using RCCO methodology to maximize efficiency of the system. The proposed system is implemented in python and achieves the highest accuracy, precision, Recall and FI-Score of 0.9929.

## VII. AUTHOR'S CONTRIBUTION

**Conceptualization:** Vimala Ithayan J, Dilip Charaan R M, Vijayanandh T, Santhoshkumar S P, Parvathi R and Sivaprakash P.

**Methodology:** Vimala Ithayan J and Dilip Charaan R M.

**Investigation:** Vimala Ithayan J and Dilip Charaan R M.

**Discussion of results:** Vimala Ithayan J, Dilip Charaan R M, Vijayanandh T, Santhoshkumar S P, Parvathi R and Sivaprakash P.

**Writing – Original Draft:** Vimala Ithayan J.

**Writing – Review and Editing:** Vimala Ithayan J and Dilip Charaan R M.

**Resources:** Dilip Charaan R M.

**Supervision:** Dilip Charaan R M, Vijayanandh T, Santhoshkumar S P, Parvathi R and Sivaprakash P.

**Approval of the final text:** Vimala Ithayan J, Dilip Charaan R M, Vijayanandh T, Santhoshkumar S P, Parvathi R and Sivaprakash P.

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